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OPTIMIZATION OF MICRO-EDM PARAMETERS USING GREY-BASED FUZZY LOGIC COUPLED WITH THE TAGUCHI METHOD

OPTIMIZACIJA PARAMETROV MIKROELEKTROEROZIJE Z UPORABO MEHKE LOGIKE V POVEZAVI S TAGUCHI METODO

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The correct selection of process parameters for the best performance output of a micro-electro-discharge machining (Micro-EDM) process is challenging because the performance measures of micro-EDM are non linear. This work aims to solve and control complex non-linear systems by applying the hybrid grey-based fuzzy logic together with the Taguchi technique in the field of micro-EDM. Input parameters, namely, the discharge current, pulse-off time and pulse-on time were selected to obtain the target responses such as the material-removal rate (*MRR*) and tool-wear rate (*TWR*). Nine experiments were performed based on the Taguchi L_9 orthogonal array. An analysis of variance was performed to find the significant contribution of the intervening process parameter in a single performance characteristic using the grey-based fuzzy-logic expert system. Multi-performance characteristics indexes (MPCIs) were analysed and the results were calculated with good accuracy.

Keywords: ANOVA, fuzzy logic, orthogonal array, grey-based Taguchi technique, electrical-discharge machining, drilling

Pravilna izbira procesnih parametrov za doseganje najboljšega izkoristka procesa mehanske obdelave z mikroelektro erozijo (angl. Micro-EDM) je izziv, ker so procesni parametri mikro-EDM nelinearni. Namen pričujoče raziskave je bil reševanje in nadzor kompleksnih nelinearnih sistemov mikro-EDM mehanske obdelave z uporabo hibridne mehke logike (Grey-based fuzzy logic) v povezavi s Taguchi metodo. Avtorji raziskave so izbrali naslednje vhodne parametre: razelektritveni tok, čas vklopa in čas izklopa impulza. Na njihovi osnovi so dobili odgovore na zastavljeni vprašanji; kakšna je hitrost odstranjevanja materiala in kakšna je hitrost obrabe orodja. Na podlagi Taguchi L9 ortogonalne matrike so izvedli devet praktičnih preizkusov mehanske obdelave z μ-EDM. Izvedli so analizo variance, podprto z ekspertnim sistemom na osnovi mehke logike, da bi ugotovili učinek intervencijskega procesnega parametra pri eni sami spremenljivki. Določili so indekse učinkovitosti (angl. MPCIs) in izračunani rezultati so bili zelo točni.

Ključne besede: analiza variance (ANOVA), mehka logika, ortogonalna matrika, robustna statistična Taguchi metoda, mikro elektroerozija (μ-EDM), vrtanje

1 INTRODUCTION

In recent technological advancements, the products are to be lighter, thinner and smaller. Many advantages arise when a part is miniaturized, such as energy and space savings, accelerating chemical reactions, attractive appearance, and cost-effectiveness.[1] The Monel 400 alloy is considered as the most promising and the most commonly used nickel-based alloy because of its excellent corrosion resistance and toughness over a wide temperature range. The Monel alloy has been extensively used in the chemical industry, food-processing industry, heat-exchanger tubes, nuclear reactors, sub marines and ship propellers.[2] The Monel alloy work hardens rapidly as it undergoes a high strain during machining. This hardening effect decreases further machining of the alloys. Therefore, it is very difficult to machine these alloys using conventional machine tools.[3] Several research works[4–6] have been carried out and reported on machining the nickel-based alloys using different conventional and non-conventional machining methods. Micro-machining is the most fundamental technology used for the production of miniaturized parts and components.[7] Micro-EDM has been known as one of the indispensible micro-machining techniques with obvious advantages of machining complex structures with high aspect ratios, high precision and accuracy irrespective of workpiece material's hardness and toughness.[8] Micro-EDM uses electrical discharge between two electrodes, and the spark from them generates such an extremely high temperature that the material is removed by vapor bubble.[9]

Many studies[1–3] were performed previously on machining nickel-based alloys with EDM and electro-chemical machining. P. Kuppan et al.[10] investigated the effect of various process variables of EDM in deep-hole drilling of Inconel 718. The objective of this study is to investigate the interaction effects of the process variables such as peak current, pulse-on time, duty factor, and electrode speed on machining characteristics. The results reveal that the material-removal rate is more influenced by the factors such as peak current, pulse-on time and duty factor. H. S. Liu et al[11] investigated the characterization of high-alloy micro-holes using micro-EDM. In this study, it was reported that the discharge current significantly affects the process. To achieve the optimum results, a proper discharge current is required. I. Ayesta et al.[12] investigated the influence of EDM variables on the machining slot in the C1023 aeronautical alloy. The objective of this study is to determine the effects of the parameters related to the discharge process (current, pulse time and voltage) on the machining rate and electrode wear. The results reveal that the discharge current and pulse-on time are the most influencing process parameters. V. Kumar et al.[13] investigated the wire-electrical-discharge machining of the Monel 400 alloy using the response-surface methodology. A high discharge energy increases the extent of the surface damage and results in large diameter craters on the machined surface. A low discharge energy and a high value of the pulse interval leads to minimum defects on the machined surface.

Trim-cut operations were performed to improve the surface integrity at high discharge-energy levels. However, EDM is a multi-input and multi-output process. Some research works were carried out to optimize the EDM process and to select the optimum process parameters for improving the performance of the process. J. Kao et al.[14] explained an experimental approach to determine the EDM-process-parameter optimization of the Ti 6Al 4V alloy using the Taguchi method and grey relational analysis by considering multiple performance characteristics, namely, the electrode-wear ratio, material-removal rate and surface roughness. The pulse duration, discharge current, open voltage and duty factor are the inputs considered. B. Pradhan et al.[15] tried to optimize the micro-EDM process using the response-surface methodology while machining Ti-6Al-4V. The observed results reveal that the pulse-on time was the foremost affecting parameter for the material-removal rate, overcut and taper, whereas the tool-wear rate was mostly affected by the peak current. In this work, we investigated the effects of the process parameters on the material-removal rate and tool-wear rate while producing micro-holes in the Monel 400 alloy using micro-EDM. Three important process parameters were studied and modeled for the material-removal rate and tool-wear rate using the grey-based fuzzy-logic method coupled with the Taguchi technique.

2 MULTI-RESPONSE OPTIMIZATION USING GREY-BASED FUZZY APPROACH

The grey-relational-analysis theory initialized by J. L. Deng[16] makes use of this technique to handle an uncertain systematic problem with only partially known information. The grey relational analysis is a method of measuring the degree of approximation among the sequences according to the grey relational grade. The theories of the grey relational analysis have already attracted the interest of researchers in various manufacturing processes that include electric-discharge machining.[17–20] In this research, the objective is to convert the complex multiple-objective optimization into a single grey-fuzzy reasoning grade. In the grey relational analysis, pre-processing of the experimental data includes the measured values of response attributes that are normalized first. During the normalization, the parameter range is restricted between 0 and 1 because of the use of different units and scales for the attributes. This process is called the grey relational generation. Next, on the basis of the normalized experimental data, the grey relational coefficient is evaluated to represent the deviation between the desired and actual experimental data. Finally, the overall grey relational grade is evaluated by taking the average of the grey relational coefficients corresponding to the selected responses. The optimum parameter combination is then determined, resulting in the highest grey relational grade.[21] The overall performance characteristic of the multiple-response performance characteristics depends on the calculated grey relational grade. The grey relational grade is calculated on the basis of the "lower-the-better", "higher-the-better" or "nominal-the-best" characteristics of each multiple response and hence, there is still some degree of unclearness about the obtained optimal result. The theory of fuzzy logic provides a means for representing the uncertainties associated with vagueness, imprecision and/or lack of information regarding the problem in hand.[22]

The theory of fuzzy logic formulated by L. A. Zadeh[23] is a proven technique and has been useful in dealing with uncertain and vague information. The definition of the objectives contains a certain degree of unclearness with vagueness. Hence, the fuzzy logic is applied to establish the optimal setting of the parameters for multiple objectives. In this way, a complex multi-objective problem is converted into a single-objective optimization problem.

2.1 Proposed methodology

The following are the procedural steps adopted to solve the multi-response optimization problem using the grey-based fuzzy logic for micro-EDM:

1. Identification of the important response parameter and key-process input parameters to be evaluated.
2. Selection of the appropriate orthogonal array to design the plan of experiment.
3. Conducting experiments as per the experimental plan.
4. Evaluation of the output response based on the experimental results.
5. Pre-processing of the raw data that is normalized for the experimental results using Equations from (1) to (3).

6. Computation of the grey-relational coefficient of the machining parameters using Equation (4).
7. Ascertaining the membership function to fuzzify the grey relational coefficient of each response and the generation of the fuzzy rule.
8. Determination of the fuzzy multi-objective outputs with a defuzzification of the output linguistic variables into crisp values representing the grey-fuzzy reasoning grade.

3 EXPERIMENTAL PART

The process parameters, selected for this investigation, were the discharge current, pulse-on time and pulse-off time as they significantly influence the EDM process performances.[10–12] Their influence on the material-removal rate and tool-wear rate was tested through a set of planned experiments based on the L_9 orthogonal array of Taguchi's design of experiments. **Table 1** shows the factors and their levels with coded and actual values. **Figure 1** shows a photographic view of the experimental EDM apparatus. The commercially obtained Monel 400 alloy having a thickness of 5 mm was used as the workpiece material. The chemical composition (mass fractions, *w*/%) of the Monel 400 alloy is as follows: C (0.047 %), Si (0.172 %), Mn (1.03 %), P (0.012 %), S (0.01 %), Cr (0.1 %), Mo (0.1 %), Fe (1.66 %), V (0.029 %), Co (0.103 %), Nb (0.1 %), Ti (0.047 %), Mg (0.031 %) and Ni (67.4 %). A brass electrode (Cu: 61.8 %, Zn: 37.2 % and impurities: 1.0 %) with a diameter 2.0 mm was selected to drill holes in the workpiece. Commercial-grade kerosene was used as the dielectric fluid and side injection of the dielectric fluid was selected.

Figure 1: Electrical-discharge-machine set-up

4 TAGUCHI TECHNIQUE

The Taguchi technique has been widely used in DOE (design of experiment), and it was employed for creating the experimental design.[24] The Taguchi technique provides standardized methods for each of the DOE application steps. It uses a special design of orthogonal arrays to study the entire process-parameter space with only a small number of experiments.[25] The aim of conducting an orthogonal experiment is to find the optimum level for each factor and to ascertain the relative importance of individual factors in terms of their main effects on the response. The experimental data is presented in **Table 2**. The data is then transformed into a signal-to-noise ratio that can be used to measure the quality characteristics. Taguchi projected three classes of objective functions such as the smaller-the-better, larger-the-better and nominal-the-best for optimizing the static problems.

Table 1: Process parameters and their levels

Parameters	Factors	Levels		
		1	2	3
Pulse-off time (μs)	A	2	3	4
Discharge current (A)	B	4	5	6
Pulse-on time (μs)	C	4	5	6

Table 2: Experimental data

Trial Nos	A	B	C	Material-removal rate	Tool-wear rate
1	1	1	1	0.00353	0.01972
2	1	2	2	0.00909	0.05390
3	1	3	3	0.01010	0.07985
4	2	1	2	0.00308	0.02246
5	2	2	3	0.00446	0.03022
6	2	3	1	0.00688	0.05934
7	3	1	3	0.00273	0.02156
8	3	2	1	0.00395	0.03404
9	3	3	2	0.00876	0.05934

5 RESULTS AND DISCUSSION

5.1 Grey-fuzzy analysis

5.1.1 Normalization of the signal-to-noise ratio

In micro-EDM, the response variables are normalized. Depending on the quality characteristics, Equation (1) is for higher-the-better and Equation (2) is for smaller-the-better.

Higher-the-better:

$$X_i(k)=\frac{Y_i(k)-\mathrm{Min}Y_i(k)}{\mathrm{Max}Y_i(k)-\mathrm{Min}Y_i(k)} \tag{1}$$

Smaller-the-better:

$$X_i(k)=\frac{\mathrm{Max}Y_i(k)-Y_i(k)}{\mathrm{Max}Y_i(k)-\mathrm{Min}Y_i(k)} \tag{2}$$

Here: $X_i(k)$ = is the value after the grey relational generation; min $Y_i(k)$ is the smallest value of $Y_i(k)$ for the k^{th} response, and max $Y_i(k)$ is the largest value of $Y_i(k)$ for the k^{th} response.

5.1.2 Computing the grey relational coefficient and grade

On the basis of the normalized experimental data, the grey relational coefficient is evaluated using Equation (3) to represent the deviation between the desired and the actual experimental data. The grey relational coefficient $\xi_i(k)$ can be calculated as:

$$\xi_i(k) = \frac{\Delta_{\min} + \zeta \cdot \Delta_{\max}}{\Delta_{0i}(k) + \zeta \cdot \Delta_{\max}} \tag{3}$$

Here $\Delta_{0i} = \left\| X_0(k) - X_i(k) \right\|$ $\Delta_{0i} = \left\| x_0(k) - x_i(k) \right\|$ the difference between the absolute values of $x_0(k)$ and $x_i(k)$; it is the distinguishing coefficient $0 \leq \Psi \leq 1$:

$\Delta_{\min} = \forall j^{\min} \in i \ \forall k^{\min} \ \left\| x_0(k) - x_i(k) \right\|$ = the smallest value of Δ_{0i}

$\Delta_{\max} = \forall j^{\max} \in i \ \forall k^{\max} \ \left\| x_0(k) - x_i(k) \right\|$ = the largest value of Δ_{0i}.

After averaging the grey relational coefficients, the grey relational grade can be computed as:

$$\gamma_i = \frac{1}{n} \sum_{k=1}^{n} \xi_i(k) \tag{4}$$

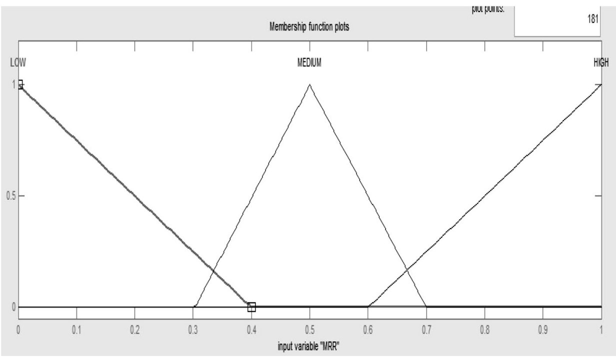

Figure 2: Membership function for the metal-removal rate

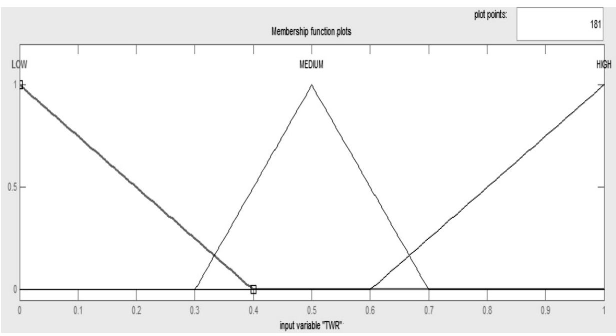

Figure 3: Membership function for the tool-wear rate

Here, n = the total number of process responses. The higher value of the grey relational grade corresponds to the intense relational degree between the reference sequence $X_0(k)$ and the given sequence $X_i(k)$.The reference sequence $X_0(k)$ represents the best process sequence. Therefore, a higher grey relational grade means that the corresponding parameter combination is closer to the optimal value. The calculated grey relational coefficients for the material-removal rate and tool-wear rate are presented in **Table 3**.

5.2 Fuzzy-logic approach

A fuzzy-logic unit comprises a fuzzifier, an interference engine and a defuzzifier. In the fuzzy-logic analysis, the methodology involves the fuzzification of the membership functions into fuzzy subsets, corresponding to linguistic terms, the derivation of fuzzy rules (if-then control rules) on the knowledge base to generate the fuzzy value, and finally, the defuzzification of the fuzzy value into a multi-performance characteristics index (MPCI).

Table 3: Normalized values and grey relational coefficients

Exp. No.	Normalized values of *MRR*	Normalized values of *TWR*	Grey relational coefficients of *MRR*	Grey relational coefficients of *TWR*
1	0.1964	0.0000	0.3828	0.3333
2	0.9194	0.7253	0.8611	0.6454
3	1.0000	1.0000	1.0000	1.0000
4	0.0922	0.0943	0.3551	0.3557
5	0.3751	0.3078	0.4444	0.4193
6	0.7063	0.7930	0.6299	0.7072
7	0.0000	0.0654	0.3333	0.3485
8	0.2823	0.3935	0.4106	0.4518
9	0.8912	0.7935	0.8212	0.7077

5.3 Fuzzification

The proposed model was developed in a MATLAB environment using the fuzzy-logic tool box. The fuzzifier converts the real value of input into fuzzy linguistics terms. Here, the values of individual grey relational coefficients of the material-removal rate and tool-wear rate are used as input variables, and the multi-performance characteristics index (*MPCI*) is considered as an output variable. For each input and output response, a triangular membership function is used. In this model, the triangular membership function is used for describing the inputs, namely, small, medium and large ones as shown in **Figures 2** and **3**. Similarly, five membership functions are mapped and they are indicated as very low, low, medium, high and very high, all being used as fuzzy subsets for the output-response grey-fuzzy reasoning grade (*MPCI*) as shown in **Figure 4**.

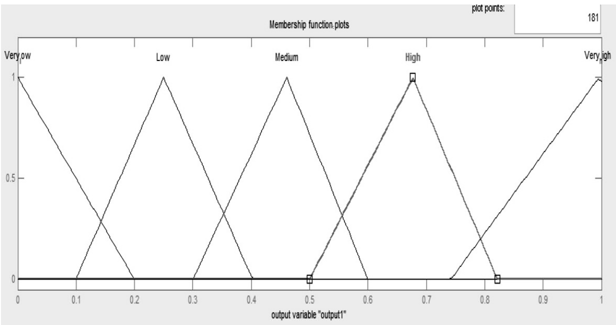

Figure 4: Membership function for the grey-fuzzy reasoning grade

5.4 Fuzzy inferencing

The next stage of the fuzzy-logic system is to derive the if-then rules to represent the relationship between the input and output variables based on linguistics terms.[26] In this study, nine control rules are written using the rule editor for the best fit of the model, which is presented in **Table 4**.

Table 4: Fuzzy rules in the matrix form

Fuzzy rule for grey-fuzzy model		Normalized value of *TWR*		
		Small	Medium	Large
Normalized value of *MRR*	Small	Medium	Low	Very low
	Medium	High	Medium	Low
	Large	Very high	High	Medium

5.5 Defuzzification

The last stage of the fuzzy model is the defuzzification process. Using the defuzzification method, fuzzy values can be combined into one single crisp output value. In this study, the fuzzy output functions are obtained using the center of the gravity method of defuzzification.[26] The formula to find the centroid of the combined outputs, Y_0, is given by:

$$Y_0 = \frac{\sum Y\mu C_0(Y)}{\sum \mu C_0(Y)} \tag{5}$$

where μ is the degree of the membership function. C_0 is the output variable. The yielded value is the final crisp output value obtained from the input variables.

In this research work, the non-fuzzy value Y_0 is called the multi-performance characteristics index (*MPCI*). To determine the optimal process conditions, it is essential to determine the largest multi-performance characteristics index among all the possible combinations of the process parameters. The mean value of the multi-performance characteristics index for each level of the response factors is then calculated as summarized in **Table 5**. As the experiments are conducted based on the Taguchi orthogonal array, it is possible to separate the effect of each machining parameter on the multi-performance characteristics index at different levels. For example, the mean of all the multi-performance characteristics indexes for the pulse-off time at levels 1, 2 and 3 can be found by averaging the fuzzy-reasoning-grade values from 1 to 3, 4 to 6 and 7 to 9, respectively. The mean values of the multi-performance characteristics indexes for the discharge current and pulse-on time are also calculated by adopting the same procedure. The mean fuzzy reasoning grades for the levels of each parameters are presented in Table 6, named the response table, which also contains the mean of the multi-performance characteristics indexes.

The ranges between the maximum and the minimum of the multi-performance characteristics index are ranked and the largest range is ranked as 1. Response factors with a large range of multi-performance-characteristic-index values for their levels have significantly more influences on the micro-EDM process. It is clear that factor B (discharge current) has the strongest effect on the material-removal rate (*MRR*) and tool-wear rate (*TWR*), followed by factor C (pulse-on time) and factor A (pulse-off time). They are regarded as the most important process factors because of their combination directly affecting the thermal-input rate. Therefore, the machining parameter settings of the third experiment are optimal for attaining the desired multiple performances simultaneously with the nine experiments. However, the relative magnitude of the effects of the machining parameters for the multiple performance characteristics still needs to be analyzed so that the optimal combinations of the machining parameter levels can be determined more clearly. The relative magnitude of the effects of the factors can be analyzed through an analysis of variance (ANOVA).

Table 5: Grey-fuzzy reasoning grades and their ranks

Exp. No.	GR grade	Rank
1	0.3333	9
2	0.7154	4
3	1.0000	1
4	0.4081	8
5	0.7280	3
6	0.6436	5
7	0.4100	7
8	0.4539	6
9	0.7586	2

5.6 Analysis of variance (ANOVA)

ANOVA is a statistical technique used to analyze experimental results. It is widely used to identify the performance of a process parameter under investigation.[27] ANOVA was used to investigate the relative effects of the response factors on the MPCIs and, as a result, the optimal combinations of the control factors could be accurately determined. In **Table 7**, the last column shows the percentage contribution of each factor

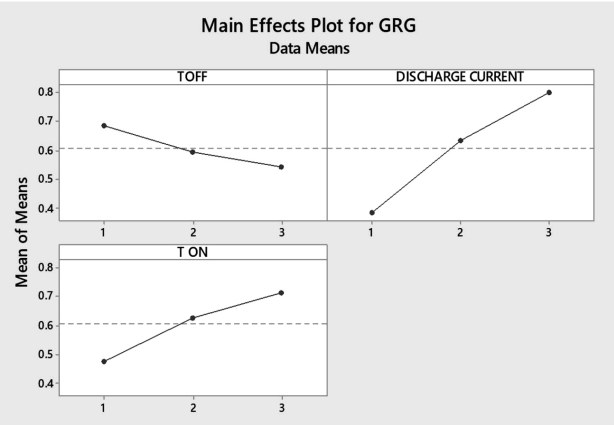

Figure 5: Graph for each level of process parameters

as the total variation, showing its influence on the result. From **Table 7**, it can be seen that the discharge current and pulse-on time are the most significant factors affecting the material-removal rate and tool-wear rate. The pulse-off time has the least effect on the material-removal rate and tool-wear rate. The larger the multi-performance characteristics index is, the better are the performance characteristics.

Table 6: Response table for the grey-fuzzy reasoning grade

Level	Pulse-off time (μs)	Discharge current (A)	Pulse-on time (μs)
1	0.6829	0.3838	0.4769
2	0.5932	0.6324	0.6274
3	0.5408	0.8007	0.7127
Delta	0.1421	0.4169	0.2357
Rank	3	1	2

Table 7: ANOVA table for the grey-fuzzy reasoning grade

Symbol	Process parameter	Degrees of freedom	Sum of squares	Mean squares	*F*-ratio	Percentage contribution
A	Pulse-off time (μs)	2	0.0318	0.01509	16.40	7.421
B	Discharge current (A)	2	0.2639	0.13195	143.42	68.62
C	Pulse-on time (μs)	2	0.0855	0.04279	46.51	21.93
E	Error	2	0.0018	0.00092	-	2.029
Total	8	0.3831	0.19156	-	100	

6 CONCLUSION

The impact of the process parameters and optimum process parameters for a micro-EDM process on multi-response performance characteristics is systematically investigated using the grey relational analysis and fuzzy logic with the Taguchi orthogonal array. The following conclusions can be made:

1. The approach of the Taguchi-based grey-fuzzy-logic analysis is an efficient productive method for optimizing multi-objective problems, predicting the material-removal rate and tool-wear rate in micro-EDM of the Monel 400 alloy.
2. From the ANOVA computations, it is revealed that the discharge current and pulse-on time are the predominant factors that affect the material-removal rate and tool-wear rate. The discharge current (68.62 %) has the main influence on the material-removal rate and tool-wear rate, followed by the pulse-on time (21.93 %) and pulse-off time (7.421 %).
3. The best performance characteristics are obtained with a discharge current of 6 A, pulse-on time of 6 μs and pulse-off time of 2 μs.

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